

Unveiling the Severity of Pedestrian Traffic Crashes in South Australia: Age-based Insights and Safety Implications

Ali Soltani ^{a,b,*}, Ahmed Jaber ^c, Hamed Najafi Kashkooli ^{d,*}, Madiha Bencekri ^e

^a College of Science and Engineering, Flinders University, Bedford Park, SA 5042, Australia

^b City Futures Research Centre, University of New South Wales, Sydney, NSW 2052, Australia

^c Department of Transport Technology and Economics, Faculty of Transportation Engineering and Vehicle Engineering, Budapest University of Technology and Economics, Műegyetem rkp. 3, H-1111 Budapest, Hungary

^d Department of Urban Planning, Shiraz University, Shiraz, Iran

^e University of Seoul, Department of Transportation, College of Urban Sciences, Seoul, South Korea

ARTICLE INFO

Keywords:

Traffic safety
Pedestrian crashes
Age-specific risks
Classification models
South Australia

ABSTRACT

Pedestrian crashes are a global safety issue impacting all age groups, and despite extensive research, understanding the severity of crashes among different age groups has remained incomplete. Older and young pedestrians represent two distinct demographics with unique vulnerabilities. This paper examines the factors that impact the severity of pedestrian crashes resulting in Killed or Serious Injuries in South Australia over ten years (2012–2020) for two age groups, namely young pedestrians (age < 18) and older pedestrians (age > 65). The study employs several descriptive and analytical methods, including logistic and Classification and Regression Tree models. The findings reveal that older pedestrians are primarily involved in fatal crashes (32 %), while their young cohorts predominantly suffer from serious injuries (30 %). Young pedestrians experience more severe consequences when vehicle speeds are below 60 km/hr, but older pedestrians suffer a greater likelihood of harm at speeds beyond 60 km/hr. Age has a role in how unique elements, such as curving roadways and damp weather, affect the intensity of the impact. Young individuals are particularly drawn to motorways and one-way highways, which are prominent areas that underscore the necessity for action. Intersections, including crossroads and one-way highways, pose significant challenges for older pedestrians, underscoring the need for safety precautions. Also, there is a negative correlation between weekend crashes and log-odds of KSI compared to weekdays, which leads to lower severity for both age groups. Customizing safety protocols for distinct age cohorts is crucial for ensuring efficient crash mitigation.

Introduction

Pedestrian crashes remain a major global safety concern, affecting individuals across all age groups [1]. Although various studies have examined factors contributing to these crashes [2–4], limited attention has been given to how crash severity differs between older and younger pedestrians. The interaction between age, road conditions, and environmental factors plays a critical role in determining crash outcomes [5]. In recent years, rising global concern over pedestrian safety has emphasized the need to distinguish the specific vulnerabilities of different age groups [6,7]. Older adults often experience physical limitations that reduce their ability to navigate traffic [3], while younger individuals may lack the cognitive and perceptual skills to respond

effectively [8]. Addressing these differences is vital for inclusive and safer urban design. According to the Organization for Economic Co-operation and Development (OECD), Australia reported a road traffic fatality rate of 4.54 per 100,000 population in 2022—ranked 18th out of 38 member countries—reflecting an 11.4 % decrease since 2013. This reduction falls short of the OECD median improvement of 20.8 % over the same period. Similarly, Australia's fatality rate per 10,000 registered vehicles stood at 0.57 in 2022, ranking 13th out of 24 nations, with a 17.2 % decline compared to the OECD median of 25.6 % [9–11]. While Australia's road safety record is not poor, the pace of improvement remains below international benchmarks.

This paper seeks to identify age-specific risk factors that influence the severity of pedestrian crashes (i.e., collisions between vehicles and

* Corresponding authors.

E-mail addresses: Ali.Soltani@flinders.edu.au (A. Soltani), ahjaber6@edu.bme.hu (A. Jaber), hmd.njf.76@gmail.com (H.N. Kashkooli), madihabencekri1@gmail.com (M. Bencekri).

<https://doi.org/10.1016/j.injury.2025.112716>

Accepted 22 August 2025

Available online 24 August 2025

0020-1383/© 2025 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

pedestrians) in South Australia. It explores how younger and older pedestrians respond differently to environmental, infrastructural, and demographic conditions such as speed limits, road alignment, lighting, and weather. This study focuses on younger (≤ 18 years) and older (≥ 65 years) pedestrians, who are especially vulnerable due to age-related physical and behavioral characteristics. To this end, we employ both statistical and machine learning techniques—including Binomial Logit Regression, Classification and Regression Trees (CART), and SHAP (SHapley Additive exPlanations)—to assess how age interacts with crash-related factors and to uncover interpretable, data-driven patterns in crash severity. By identifying the most influential predictors across age groups, this research provides a foundation for developing targeted safety strategies, inclusive urban planning measures, and age-appropriate educational interventions, ultimately contributing to the reduction of pedestrian injuries and fatalities through more responsive transport policies and infrastructure design in Australia.

Literature review

The functional capacity of individuals, observed over three distinct life stages - early life, adult life, and older age, exhibits an inverted U-shaped trajectory. This pattern reflects a lower capacity during life's initial and final stages [12]. The early life stage is characterized by increased functional capacity, primarily driven by physical and cognitive development, skill acquisition, and overall health enhancement. Upon reaching adulthood, individuals typically experience their peak functional capacity. However, a decline in functional capacity is observed as they transition into the older age stage. This decline is attributed to reduced physical activity, the onset of chronic diseases, and the natural processes associated with biological aging [13]. The literature reveals that age plays a pivotal role in shaping the outcomes of pedestrian crashes, and these high-risk pedestrian behavioral patterns likely stem from age-dependent neurobiological changes in the brain that impair cognitive flexibility and amplify risky decision-making tendencies [14].

Several studies exhibit that older pedestrians (aged 65–75 years) have a greater probability of being involved in pedestrian crashes [4, 15–18]. Also, injury severity increases with age among older people victims of pedestrian traffic crashes [19–21], which is due to factors such as reduced mobility, diminished vision or hearing, and slower reaction times significantly contribute to higher crash severity [3,22]. Older people pedestrians are at increased risk of injury and death from vehicle crashes due to physical fragility that occurs with age, such as loss of muscle bulk and bone density [23,24]. Studies have consistently shown that, compared to younger adults, older adults (65+) exhibit substantially slower reaction times and diminished capabilities to respond quickly and effectively to sudden or unexpected hazardous events while driving or walking [4,25–27].

Various factors, such as individual characteristics, tasks, and environmental constraints, contribute to the road-crossing behavior of older adults [28]. Normal age-related deterioration in selective and divided attention, visual acuity, contrast sensitivity, and other perceptual faculties may considerably impair older adults' hazard perception skills and situational awareness while navigating traffic environments [29]. Furthermore, research indicates that older pedestrians often demonstrate unsafe road crossing decisions and behaviors, including inadequate visual scanning for oncoming vehicles before crossing, difficulty accurately judging approaching vehicle speeds, longer fixations, and reluctance to cross streets against traffic lights or signals even when safe to do so [11,30,31]. Older participants shifted their decision criteria towards more conservative judgments, leading to considerable behavioral improvements. Oxley et al. [32] found that older adults faced challenges in processing both the distance and speed of vehicles under time constraints, resulting in unsafe crossing decisions even with increased time for inspection. Older pedestrians often face distinct challenges due to age-related physical limitations that compromise their

ability to navigate streets safely [10]. Taken together, the array of age-related declines in sensory, perceptual, cognitive, and behavioral capabilities help explain why older adults are at substantially higher risk for crashes as both drivers and pedestrians compared to younger age groups, despite their typically lower exposure in terms of miles driven annually [33]. Older pedestrians are less likely to be involved in crashes during late evenings or early mornings, on curved roads, in adverse weather, with single vehicles, or at high speeds [34]. Instead, they were more frequently involved in crashes at intersections, including failure to yield, crashes with unseen objects, and disregarding stop signs or signals. According to Haleem et al. [35], in signalized and non-signalized intersections, old pedestrians were associated with a higher probability of severe injuries compared to the young age group, mainly due to their weak physical conditions. However, very old pedestrians experience a greater severity risk at signalized intersections than non-signalized intersections [36–38]. Studies have also indicated that comorbidities and pre-existing health conditions among older adults escalate the risk of severe outcomes in pedestrian crashes [10].

Conversely, youngsters face vulnerabilities as pedestrians, contributing to their high risk of being struck by vehicles [39]. Younger pedestrians, particularly children, exhibit vulnerabilities stemming from their developmental stage, which may limit their cognitive and perceptual abilities in understanding and responding to traffic situations, such as crossing the streets, gauging traffic speeds, and focusing attention on potential hazards [40–42]. Younger children exhibit poor impulse control and have yet to develop healthy fears of traffic that normally curb risky crossing behaviors [43]. Developmental immaturity in perceptual and motor skills hampers children's coordination and ability to react quickly to an approaching vehicle [44]. They may also display less cautious behavior when crossing roads, influenced by social cues and conformist behavior [41]. Additionally, their smaller stature and limited visibility to drivers further amplify the severity of crashes involving younger pedestrians [45]. Time of day and season contribute to the risk of pedestrian trauma in young people, with reduced visibility and school pick-up times playing a significant role [46]. Older children may knowingly engage in several unsafe pedestrian behaviors [47]. Adolescents aged 13–14 are more at risk when in groups, particularly boys, who tend towards more risky behavior [48]. According to [49], significant improvements in both short- and long-term benefits from the training can be observed.

Comparing the two groups reveals that those under 18 and over 65 are more affected by the neighborhood environments than other age groups, with factors such as parks, convenience stores, and restaurants playing a role in reducing the severity of pedestrian injuries [50]. Older adults have a higher injury risk than younger people, while children have a lower risk at lower collision speeds but a higher risk once a threshold is exceeded [51]. There are differences in injury severity relative to the pedestrian's age, with young pedestrians more likely to suffer serious injury in school zones. In contrast, older people pedestrians are more likely to suffer fatal injuries in areas with more traffic signals [52]. The older adults' and young adults collision avoidance behaviors with another pedestrian are different as older adults exhibited riskier avoidance behaviors, passing closer to another pedestrian compared to interactions between two young adults [53]. Regarding sociodemographic factors, pedestrian crash victims in areas with higher low-income and minority populations tend to be younger compared to those in areas with different demographics through a study conducted in Chicago [54]. The study of age and gender-specific temporal and spatial patterns in crash occurrences revealed distinct influences of pedestrian age on crash distribution and different crash patterns between genders and age groups in Melbourne, including varying high-risk areas throughout the day and night [55]. Ulak et al. [56] revealed significant heterogeneous effects of predictors. They emphasized the influence of specific facilities like hospitals or supermarkets on crash rates, with varying impacts during weekdays versus weekends in Florida. In summary, the literature underscores that age-specific vulnerabilities

significantly contribute to differences in crash severity between older and younger pedestrians (Table 1).

Data and methodology

Case study & data

With 4.54 deaths per 100,000 people in 2022, Australia was ranked 18th out of the 38 OECD countries in terms of its death rate due to road crashes [9]. Regarding the general patterns from 2011 to 2021, there are variations in the number of male pedestrians admitted to hospitals, ranging from 1189 in 2020 to 1581 in 2011. The diversity highlights the ever-changing character of serious pedestrian crashes throughout the years. Furthermore, there is an apparent disparity between genders, as male pedestrians account for a significantly greater average of 1468.09 yearly hospitalizations, in contrast to females, who have an average of 1125.64. The number of hospitalizations for female pedestrians shows distinct peaks, with a peak of 1228 in 2017. The analysis of age distribution reveals distinct susceptibilities, with males in the 65 and above age group consistently exhibiting elevated hospitalization rates (19.26 % to 28.82 %) compared to individuals aged 16 to 65 (ranging from 16.99 % to 20.94 %). Similarly, females in the 65 and older age group continuously have higher rates of Annual hospitalizations, ranging from 26.27 % to 28.85 %, compared to the 16 to 65 age group, with rates ranging from 12.01 % to 17.48 %. The proportion of pedestrian hospitalizations relative to overall road user hospitalizations is greater for females (average of 8.59 %) than males (average of 6.05 %), highlighting the gender-specific effects.

Furthermore, there are clear vulnerabilities that are particular to different age groups. This is seen in the breakdown of male road user hospitalizations, where those aged 65 and older continuously have greater percentages compared to those aged 16 or younger. Similarly, the proportion of hospitalizations for female road users who are 65 years and older is significantly greater, highlighting the special risks associated with this age group [9]. This research focuses on South Australia, which has a population of nearly 1.7 million, accounting for 7.14 percent of Australia's overall population. Based on the Australian census data, the female population of South Australia accounts for 50.7 %, while the male population accounts for 49.3 %. With a population density of 1.62 inhabitants per square kilometer, it ranks as the sixth most populated state in Australia. Reflecting on the past ten years, South Australia has seen a consistently stable population growth rate, ranging from 0.23 % to 1.21 %. This has resulted in an annual increase of 4000 to 20,000 individuals added to the population [58]. The detailed crash data is retrieved from the South Australian Government Data Directory [59]. Fig. 1 illustrates the geographical distribution of pedestrian crashes in urban and rural areas of South Australia.

In analyzing the data spanning from 2012 to 2022 (with no significant changes observed post-COVID), this study focuses on understanding the dynamics of pedestrian crashes, specifically categorizing individuals into two distinct groups: the young (aged ≤ 18 years) and the older (aged ≥ 65 years) pedestrians. Table 2 presents the breakdown of pedestrian crash severity across various age categories. The data displays the frequencies of crashes categorized by severity levels: Fatal, MI (Moderate Injury), and SI (Slight Injury). Among those aged 65 and above, there is a significantly greater incidence of fatal collisions in comparison to other age groups, suggesting a heightened vulnerability to severe consequences for older pedestrians. In contrast, the age range of 0–18 had the most significant SI crashes, indicating a greater incidence of relatively major injuries among younger pedestrians. The incidence of moderate injury (MI) crashes has a reasonably uniform pattern across different age cohorts, with a marginal decline observed in the 65+ age group.

Fig. 1 illustrates the spatial distribution of pedestrian crashes across both urban and rural areas of South Australia over multiple time periods, segmented into five intervals: 2012–2014, 2014–2016, 2016–2018, 2018–2020, and 2020–2023. The crash severity levels are categorized as: 2 (MI, green), 3 (SI, orange), and 4 (Fatal – red). In urban areas, particularly within the Adelaide metropolitan region, the central business district (CBD) and surrounding suburbs exhibit the highest density of pedestrian crashes across all time periods. Fatal and serious injury crashes are notably clustered along major arterial roads and intersections, with this concentration remaining relatively stable over time, indicating persistent high-risk zones for pedestrians. In contrast, rural and regional areas show a more dispersed crash pattern, primarily along high-speed roads and highways. While fewer in number compared to urban zones, serious and fatal pedestrian crashes still occur frequently along main transport routes and rural town centers. Temporal analysis reveals no significant reduction in crash density within urban areas over the observed intervals, suggesting ongoing safety challenges despite potential interventions. Similarly, rural crash distribution remains consistent, with minor fluctuations in the locations of serious and fatal incidents. The lower panels of the figure, focusing on the main road network, further emphasize that severe crashes often occur along key transport corridors connecting urban and rural regions. This highlights that even outside dense city zones, pedestrians face significant risks, particularly where vehicle speeds are higher and pedestrian infrastructure is limited.

Methods

This study employs a multi-method analytical framework, combining Binomial Logistic Regression, Classification and Regression Tree (CART), and SHAP (SHapley Additive exPlanations) to investigate the

Table 1
Summary of involving risk factors between young and older pedestrians.

Main Theme	Risk Factor	Young Pedestrians (0–18)	Older Pedestrians (65+)	Reference
Individual Characteristics	Cognitive abilities	Less developed; poor impulse control; lack of traffic safety awareness	Age-related decline in selective/divided attention, hazard perception	[29,32,40,42,42,45,57]
	Perceptual skills	Immature; difficulty judging speeds, distances	Reduced visual acuity, contrast sensitivity, and overall perceptual capabilities	[11,29–32,39,44]
	Motor skills	Underdeveloped coordination and reaction time	Slower reaction times; reduced mobility	[3,22,28,44]
	Behavioral patterns	Impulsiveness, distraction, risky road crossing	Reluctance to cross against signals; inadequate scanning for traffic	[43,57]
Environmental Factors	Physical traits	Small stature; limited visibility to drivers	Frailty: Pre-existing conditions increase the severity	[45]
	Socioeconomics	Higher risk in low-income, minority areas	N/A	[54]
	Intersection crashes	Risk-taking behaviors	Failure to yield; disregarding signals	[34]
	Adverse conditions	N/A	Less likely to be involved in crashes at night, in bad weather	[34]
	Speed considerations	Inadequate adaptation to vehicle-pedestrian distance and vehicle speed	Difficulty judging vehicle speeds	[32]

Source: Authors.

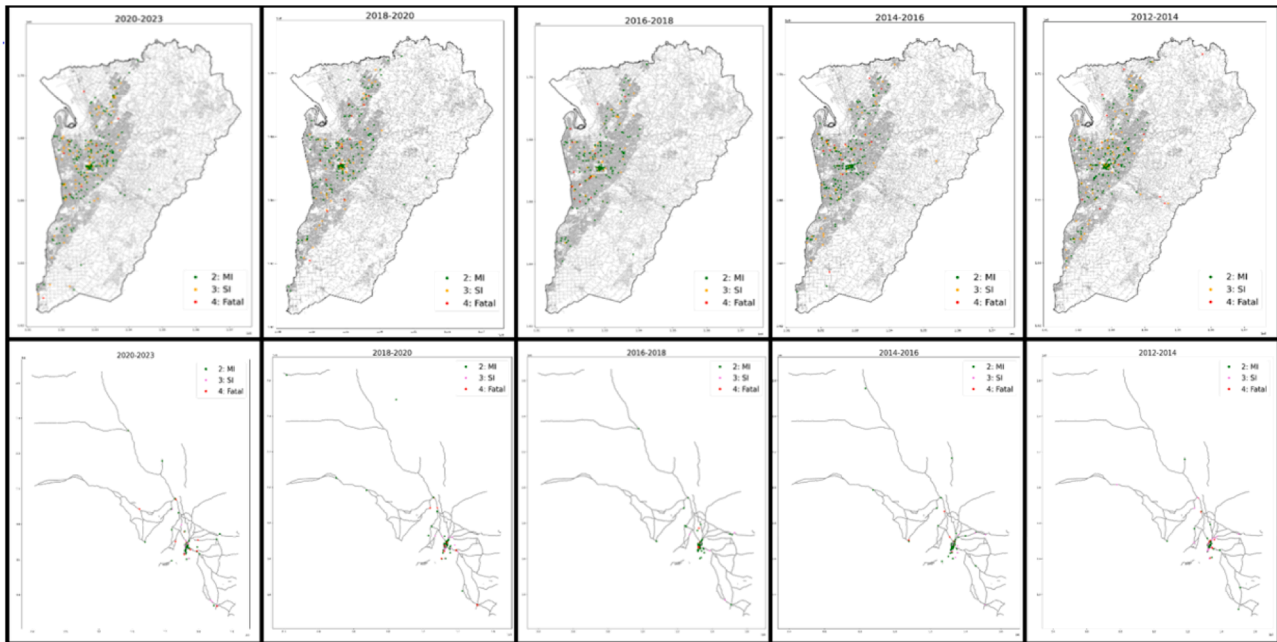


Fig. 1. Distribution of pedestrian crashes in urban and rural areas of South Australia (Source: Authors).

Table 2
Pedestrian crash severity across age categories in South Australia.

Severity /Age group	0–18	19–30	31–50	51–65	65+
Fatal (Percent)	10	19	29	10	32
MI (Percent)	24	24	21	13	18
SI (Percent)	30	25	21	12	12

Source: Authors.

factors influencing the severity of pedestrian crashes. These methods are selected for their complementary strengths in capturing linear associations, identifying complex interactions, and enhancing model interpretability. Binomial logistic regression serves as a foundational tool for statistically estimating the probability of a crash resulting in a Killed or Seriously Injured (KSI) outcome. This method is especially suitable for assessing the linear effects of predictor variables—such as speed limit, road conditions, time of day, or age—on crash severity. It provides interpretable coefficients in the form of odds ratios, allowing for a clear understanding of how each variable increases or decreases the likelihood of severe outcomes. CART analysis uncovers non-linear relationships and interaction effects that may not be evident in regression models. The decision tree algorithm segments the dataset into homogeneous subgroups based on variable thresholds, identifying high-risk scenarios through easily interpretable "if-then" logic. This makes it particularly useful for detecting context-specific combinations of risk factors, such as specific road types, pedestrian actions, or lighting conditions, that increase the likelihood of severe injuries. CART's visual structure also enhances accessibility for policymakers and urban designers. Additionally, a *t*-test was conducted to evaluate temporal differences in crash patterns between the pre-and post-COVID periods (2012–2020 vs. 2020–2022), revealing statistically significant changes ($t = 5.438, p < 0.000$). To ensure model reliability, multicollinearity was assessed using the Variance Inflation Factor (VIF), with a threshold of 7.5 used to exclude highly correlated variables.

SHAP is a model-agnostic interpretability technique derived from cooperative game theory. It is designed to quantify the contribution of each variable to a model's output. Unlike traditional variable importance metrics, SHAP offers global insights (overall feature importance across the dataset) and local explanations (variable impact for

individual predictions) [60,61]. SHAP values are computed for each observation, capturing the magnitude and direction of each feature's influence on the predicted probability of a severe crash. The features are then ranked using their mean absolute SHAP values, reflecting their average contribution across all predictions. This method ensures fairness and robustness by evaluating each variable within all possible feature combinations. In this study, variables such as Age, Speed Limit (Area-Speed), and Nighttime conditions (Night_dummy) consistently ranked among the top predictors of crash severity. The SHAP framework strengthens the interpretability of machine learning outputs and supports evidence-based decision-making for policy development, infrastructure planning, and pedestrian safety programs. Fig. 2 presents the study's Methodological process.

Binomial regression model

The binomial regression model includes the binary target variables of either KSI or slight injuries. This model relies on several assumptions, including the independence of observations and linearity in the log-odds of the probability of success. These assumptions underpin the validity of the results generated by the model. The mathematical equation typically takes the form:

$$P = \frac{\exp(b_0 + \sum_{i=1}^n b_i x_i)}{1 + \exp(b_0 + \sum_{i=1}^n b_i x_i)} \quad (1)$$

where:

- P probability of a KSI injury;
- i risk factor;
- b_0 constant (intercept of the regression line);
- b_i coefficient of risk factor i ;
- x_i binary variable of risk factor i , $x_i \in \{0, 1\}$;
- n the number of risk factors.

The model parameters were estimated using Maximum Likelihood Estimation (MLE), a standard method for binomial regression. This process allows us to obtain the coefficients associated with each independent variable, which are interpreted as the effect of a unit change in that variable on the log-odds of the event occurring. Various statistics were considered to assess the model's goodness of fit, such as the likelihood ratio test, Akaike information criterion (AIC), Bayesian information criterion (BIC), and deviance. These measures help evaluate how

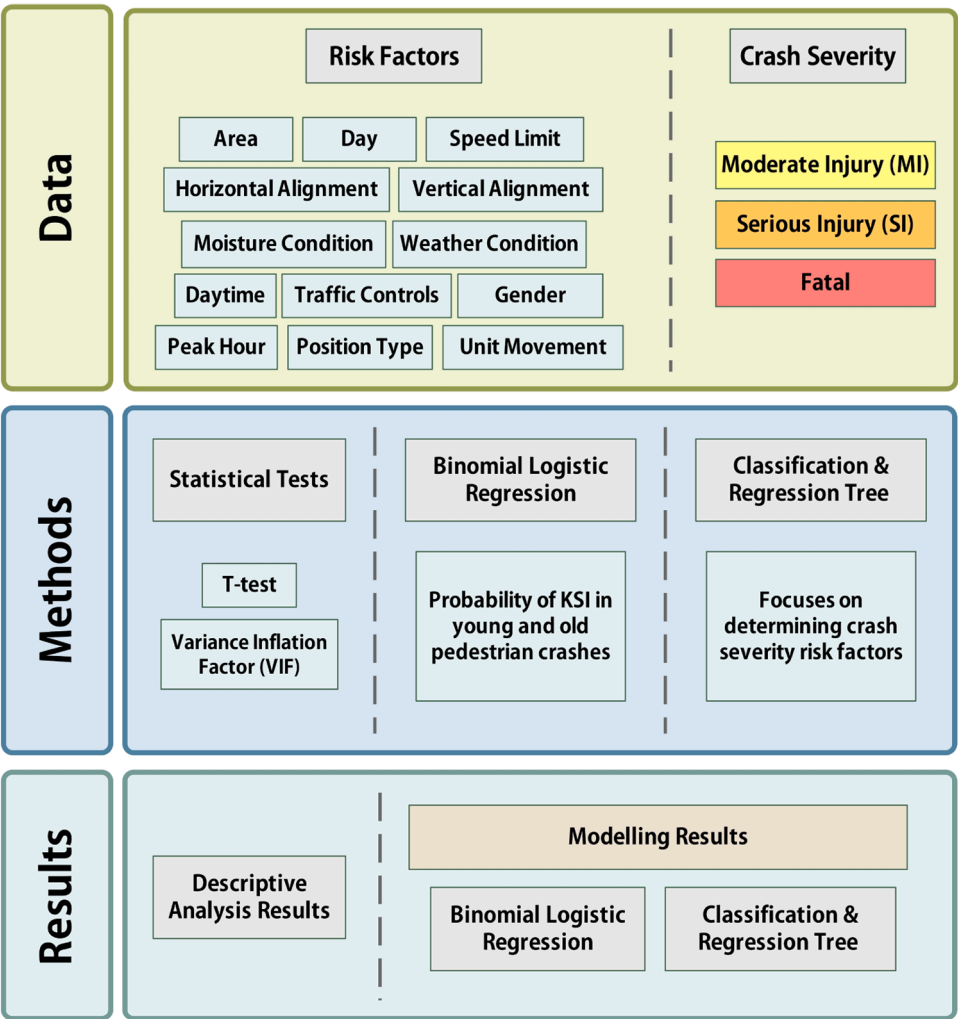


Fig. 2. Methodological process (Source: Authors).

well the model aligns with the observed data. Assumptions checking was an essential step in the analysis, where multicollinearity was examined.

Classification & regression tree (CART)

Classification & Regression Tree (CART) is a widely recognized algorithm known for its capability in predictive modeling, offering high accuracy, stability, and interpretability [62]. It allows us to discover relationships between variables and present categorical results with clear explanations. The core idea behind CART is to divide a data set into homogeneous subsets, resulting in pure branches belonging to the same target node or class. CART operates on two key pillars, “Purity” and “Balance.” The Gini index assesses purity, a measure of equality ranging from 0 (perfect equality) to 1 (maximum inequality). Balance ensures an even population distribution among the decision tree branches [63]. In this study, the focus is on understanding the factors influencing injury severity in pedestrian crashes. The CART model is specifically examined since crash severity is a variable with an ordered scale. Developed by [64], CART can handle discrete and continuous variables. A classification tree is constructed when dealing with discrete variables, while a regression tree is used for continuous variables. The CART algorithm employs the Gini index as its splitting criterion, aiming to minimize impurity and create homogeneous subsets. This index is calculated as the summation of class proportions for classes present at a node, with a Gini index of 0 indicating that all records in a node belong to the same class. CART’s approach to model construction involves binary splits and, if necessary, pruning to eliminate unnecessary branches, ultimately

enhancing the model’s interpretability and performance. The exclusive focus is on the CART model to extract and evaluate the main factors impacting injury severity in pedestrian crashes.

Results

Descriptive analysis results

The dataset includes detailed information on crash events, such as location, day type, speed limit, environmental conditions, lighting, traffic controls, and pedestrian demographics. It also captures key roadway and behavioral variables relevant to crash severity. Horizontal alignment describes road curvature (straight, curved with open or obscured view), and vertical alignment reflects elevation changes (level, slope, crest, or bottom of hill). Position type indicates whether the road was divided or undivided, and unit movement refers to the pedestrian’s action at the time of the crash (e.g., crossing without control, walking along the road). Fig. 3 summarises these variables with frequency percentages.

For young pedestrians, the majority of crashes occurred in metropolitan areas (80.7 %), followed by country areas (12.5 %) and city areas (6.8 %). Among older pedestrians, a similar trend is observed, with most crashes happening in metropolitan areas (81.0 %), followed by country areas (11.5 %) and city areas (7.5 %). Young pedestrians were involved in more weekday crashes (81.6 %) compared to Weekend/Holiday (18.4 %). Similarly, older pedestrians had a higher frequency of weekday

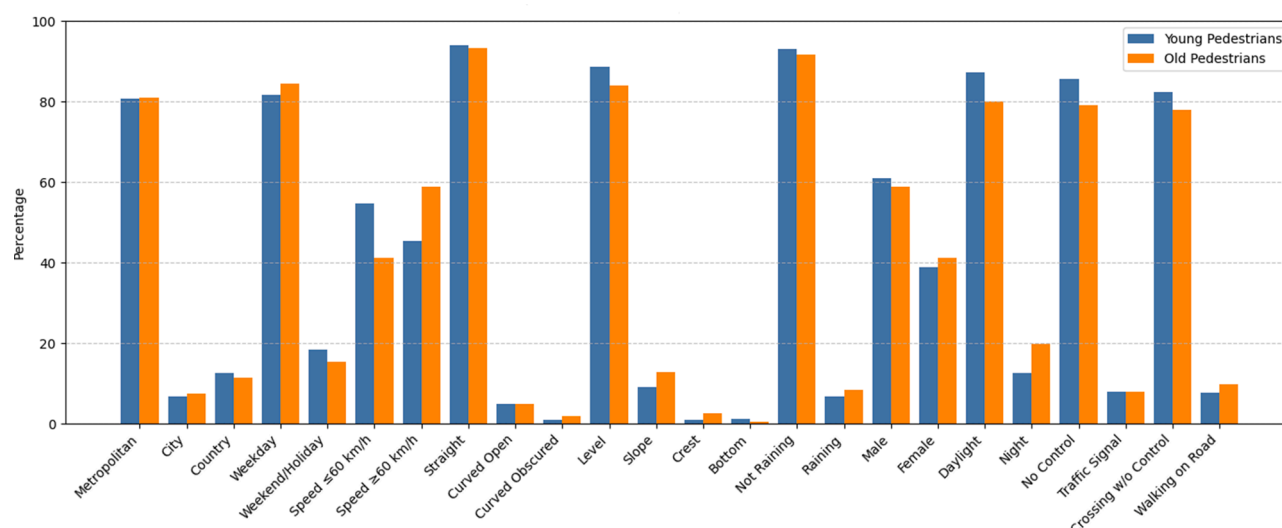


Fig. 3. Crash frequency for young pedestrians versus old pedestrians (Source: Authors).

crashes (84.5 %) than on Weekend/Holiday (15.5 %). Young pedestrians had a higher proportion of crashes where the speed was <60 km/h (54.7 %) compared to 60 km/h or more (45.3 %). In contrast, older pedestrians had a higher percentage of crashes at higher speeds, with 58.8 % occurring at 60 km/h or more and 41.2 % at speeds <60 km/h. Both young and old pedestrians were primarily involved in crashes on straight roads. For young pedestrians, 94.1 % of crashes occurred on straight roads, while for old pedestrians, it was 93.4 %. Crashes on curved roads with obscured views were rare for both groups, with only 0.9 % for young and 1.8 % for old pedestrians. Crashes on curved roads with open views were slightly more common for young pedestrians (5.0 %) than old pedestrians (4.9 %). Young pedestrians were involved in most crashes on level terrain (88.7 %), followed by sloped terrain (9.2 %). Only a small proportion of crashes occurred at the bottom of a hill (1.2 %) or the crest of a hill (0.9 %). A similar pattern was observed for older pedestrians, with most crashes happening on level terrain (84.1 %). However, a slightly higher percentage of crashes occurred on sloped terrain (12.8 %), and there were fewer crashes at the bottom of a hill (0.4 %) or the crest of a hill (2.7 %) compared to young pedestrians. Most crashes involving young and old pedestrians occurred under dry conditions. For young pedestrians, 91.3 % of crashes happened in dry conditions, while for old pedestrians, it was 89.8 %. Wet conditions were less common but still notable, with 8.7 % of young pedestrian crashes occurring in wet conditions, compared to 10.2 % for old pedestrians.

A relatively small percentage of crashes occurred in rainy weather for both age groups. For young pedestrians, 6.8 % of crashes happened in the rain, while for old pedestrians, it was 8.4 %. Most crashes occurred when it was not raining, with 93.2 % for young pedestrians and 91.6 % for old pedestrians. Among young pedestrians, the most common position type for crashes was “Not divided” (48.8 %). “Divided” (33.2 %) was the old pedestrians’ most common position type. In terms of gender distribution among young pedestrians, there were more males (61.1 %) involved in crashes compared to females (38.9 %). A similar trend is observed among old pedestrians, with a higher percentage of males (58.8 %) involved in crashes than females (41.2 %). Most crashes involving young and old pedestrians occurred during daylight hours. For young pedestrians, 87.3 % of crashes happened during daylight, while for old pedestrians, it was 80.1 %. Crashes at night were less frequent for both groups, with 12.7 % for young pedestrians and 19.9 % for old pedestrians.

Regarding traffic controls at the crash location, most crashes occurred without traffic controls for both age groups. For young pedestrians, 85.6 % of crashes happened where there were no traffic controls, and for old pedestrians, it was 79.2 %. Crashes at locations with

traffic signals were relatively common, accounting for 8.0 % of young pedestrian crashes and 8.0 % of old pedestrian crashes. During the morning peak hours, a small percentage of crashes occurred for young (2.8 %) and old (3.5 %) pedestrians. Most crashes for both age groups happened outside of the morning peak hours. Similarly, during the afternoon peak hours, a small percentage of crashes occurred for young (5.0 %) and old (1.3 %) pedestrians. For young pedestrians, the most common unit movement at the time of the crash was “Crossing without Control” (82.3 %), followed by “Walking on Road” (7.7 %). Among old pedestrians, “Crossing without Control” (77.9 %) was also the most frequent unit movement, followed by “Walking on Road” (9.7 %).

Modelling results

Binomial regression

Table 3 presents the coefficients from a Binomial Logistic Regression Model for both pedestrian age groups, Young and Old, involved in crashes, offering crucial insights into the factors influencing the likelihood of KSI (Killed or Seriously Injured) crashes within this age group. Coefficients (b) and the statistical significance (p) of risk factors have been provided, in which positive b indicates higher risk and negative b indicates lower risk compared to the base condition ($b = 0$). $\exp(b)$ gives the odds ratio of a significant injury compared to base risk factors. Accordingly, the odds ratio is equal to 1 in the case of the base risk factor. For the young group, the area coefficients represent the effect of being in a metropolitan or country area on young pedestrians’ log-odds of KSI crashes. The positive coefficient (0.067) for “Metropolitan” suggests that crashes in metropolitan areas are associated with higher log-odds of KSI compared to the reference category (City). The negative coefficient (−0.64) for “Country” suggests that crashes in country areas are associated with lower log-odds of KSI compared to the reference category. The coefficient of the weekend (−0.165) represents the lower effect of crashes occurring on weekends (compared to weekdays). Speed Category coefficient (0.142) represents the effect of crashes involving speeds <60 km/hr (compared to 60 km/hr or more) on the log-odds of KSI crashes for young pedestrians. The negative sign for “Curved, View Obscured” in the horizontal alignment’s coefficient suggests that crashes on curved roads with obscured views are associated with lower KSI. However, none of the vertical alignment coefficients have a substantial effect, as indicated by values close to zero.

The wet moisture condition coefficient (−0.31) represents the effect compared to dry conditions. Compared to daytime, the night coefficient (−0.224) suggests that crashes at night are associated with lower log-odds of KSI. The positive control coefficient for “Roundabout”

Table 3
Pedestrian crashes severity based on binomial logistic regression model.

Term	Young Group (0–18)					Older Group (65+)				
	Coeff	SE Coeff	Z-Value	P-Value*	VIF	Coeff	SE Coeff	Z-Value	P-Value	VIF
Constant	1.09	0.534	2.04	**		0.76	0.722	1.05	*	
Stats Area										
Metropolitan	0.067	0.472	0.14		3	−0.603	0.657	−0.92	*	3.1
Country	−0.64	0.541	−1.18	*	2.9	−0.604	0.754	−0.8	*	2.88
Day Category										
Weekend	−0.165	0.289	−0.57	*	1.07	−0.366	0.402	−0.91	*	1.08
Speed Category										
<60	0.142	0.244	0.58	*	1.17	0.65	0.325	2	**	1.28
Horizontal Align										
curved, view obscured	−0.55	1.27	−0.43	*	1.05	−1.04	1.24	−0.84	*	1.11
curved, view open	0.005	0.576	0.01		1.06	−0.38	0.679	−0.56	*	1.11
Vertical Align										
Bottom of Hill	0.24	1.15	0.21		1.02	14	325	0.04		1
Crest of Hill	13	265	0.05		1	0.001	0.926	0		1.16
Slope	−0.058	0.393	−0.15		1.04	0.193	0.448	0.43		1.11
Moisture Condition										
Wet	−0.31	0.4	−0.78	*	1.05	−0.832	0.515	−1.62	*	1.07
Day/Night										
Night	−0.224	0.335	−0.67	*	1.1	−0.946	0.379	−2.49	***	1.09
Traffic Controls										
Roundabout	0.83	1.09	0.77	*	1.01	0.135	0.778	0.17		1.06
Sign	0.151	0.568	0.27		1.06	−0.275	0.518	−0.53	*	1.07
Signal	0.162	0.443	0.37		1.08	0.389	0.543	0.72	*	1.09
Gender										
Male	−0.217	0.236	−0.92	*	1.02	−0.104	0.297	−0.35		1.07
Peak Hours										
AM Peak (Yes)	13	153	0.08		1	−1.036	0.797	−1.3	*	1.04
PM Peak (Yes)	0.922	0.658	1.4	*	1.05	1.24	1.32	0.94	*	1.13

* <0.1, ** <0.05, *** <0.01.

Source: Authors.

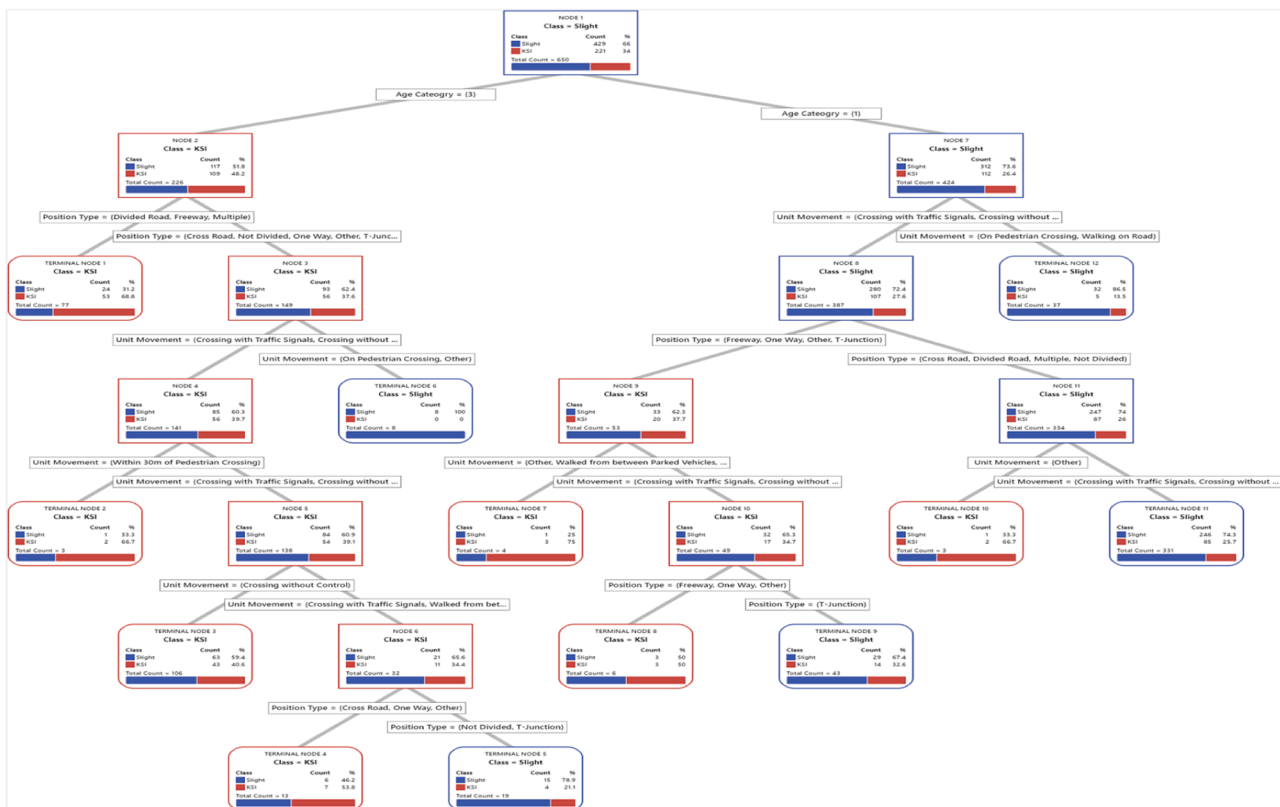


Fig. 4. CART Output (Source: Authors).

suggests that crashes at roundabouts are associated with higher log-odds of KSI. The coefficients for “Sign” and “Signal” are close to zero, indicating minimal effects. The gender coefficient (−0.217) represents the effect of gender (male compared to female). The AM peak coefficient (0.08) represents the effect of crashes occurring during the morning peak hours (compared to non-peak hours). The coefficient is close to zero, indicating a minimal effect. On the other hand, The PM peak coefficient (0.922) represents the effect of crashes occurring during the afternoon peak hours (compared to non-peak hours). The positive coefficient suggests that crashes during afternoon peak hours are associated with higher log-odds of KSI. For older pedestrians, notable coefficient values and interpretations include the “Constant” (0.76), representing the baseline log-odds of KSI crashes when all other predictors are zero. Coefficients for factors like “Metropolitan and Country” (−0.603, −0.604) indicate that crashes in these areas are associated with reduced log-odds of KSI compared to the city. “Weekend” (−0.366) suggests that crashes occurring on weekends have lower log-odds of KSI than on weekdays. “Speed Category” (0.65) shows that crashes at speeds <60 km/hr are linked to higher log-odds of KSI. “Horizontal Alignment,” especially “Curved, View Obscured,” has a negative coefficient, indicating lower KSI odds in such situations. “Vertical Alignment” coefficients are close to zero, suggesting minimal impact. “Moisture Condition” (−0.832) suggests that wet road conditions are associated with lower KSI odds. “Day/Night” (−0.946) indicates that nighttime crashes have lower KSI odds. “Traffic Controls” coefficients have minimal impact. “Gender (Male)” (−0.104) suggests that male involvement in crashes is linked to lower KSI odds. AM Peak (−1.036) indicates lower KSI odds during morning peak hours, while PM Peak (1.24) suggests higher KSI odds in the afternoon peak.

CART model results

Crash severity was employed as the dependent variable, and CART analysis was conducted to model the relationships between the independent variables (Fig. 4). The resulting decision tree had a depth of 7, 12 terminal nodes, and 11 nodes in total.

For the young pedestrians, here is an elaboration of the cases:

Case 1: KSI crashes are more likely to occur in the following condition:

- The position is at a crossroads, on a divided road with multiple lanes or a non-divided road.

Case 2: KSI crashes are more likely to occur under the following circumstances:

- The position is on a freeway, a one-way road, or at a T-junction.
- The unit movement involves “Alighted from Parked Vehicle,” “Walked from between Parked Vehicles,” or occurs within 30 m of a Pedestrian Crossing.

Case 3: KSI crashes are more likely to occur when the situation matches these criteria:

- The position is on a freeway or a one-way road.
- The unit movement involves “Crossing with Traffic Signals” or “Crossing without Control.”

This presentation highlights the conditions under which KSI crashes are more likely to happen in different cases based on the position and unit movement data.

For the old pedestrians, here is an elaboration on the cases:

Case 1: KSI crashes are more likely to occur under the following conditions:

- The position is on a freeway, a divided road with multiple lanes.

Case 2: In Case 2, KSI crashes are more likely to occur when the situation matches these criteria:

- The position is at a crossroads, on an undivided, one-way, or T-junction road.
- The unit movement includes being within 30 m of a Pedestrian Crossing or crossing without control.

Case 3: In Case 3, KSI crashes are more likely to occur when the situation corresponds to the following conditions:

- The position is at a crossroads or on a one-way road.
- The unit movement involves crossing with traffic signals, walking between parked vehicles, or walking on the road.

The tree analysis reveals that both age groups are more susceptible to KSI crashes at crossroads (**Case 1: Young; Case 2, 3: Old**) and one-way roads (**Case 2, 3: Young; Case 1, 3: Old**). Furthermore, situations where the unit movement involves crossing without control (**Case 3: Young; Case 2: Old**) or within 30 m of a pedestrian crossing (**Case 2: Young; Case 2: Old**) pose a risk to both groups. However, there are also notable differences. For young pedestrians, KSI crashes are more likely to occur on divided roads with multiple lanes or undivided roads (**Case 1, 2**). In contrast, older pedestrians are more likely to experience these crashes on freeways or divided roads with multiple lanes (**Case 1**). Additionally, the unit movement “Alighted from Parked Vehicle” and “Walked from between Parked Vehicles” are identified as risk factors for young pedestrians (**Case 2: Young**), whereas for older pedestrians, the risk factors include “Crossing with Traffic Signals” and “Walking on the Road” (**Case 3: Old**). This presentation highlights the conditions under which KSI crashes are more likely to happen in different cases based on the position and unit movement data.

Classification results

The comparative table highlights the performance and characteristics of four supervised machine learning algorithms—Logistic Regression, Decision Tree, Random Forest, and K-Nearest Neighbors (KNN)—in predicting crash severity. Among these, **Random Forest** emerged as the most accurate model, achieving an accuracy of 65 % and a weighted F1-score of 62 %, indicating its ability to handle complex relationships and variability in the data. However, its performance comes at the cost of increased computational time and lower interpretability compared to simpler models. While less accurate at 62 %, logistic regression stands out for its simplicity and high interpretability, making it suitable for scenarios requiring straightforward model insights. **Decision Tree** compromises interpretability and performance, offering slightly better accuracy (63 %) than Logistic Regression and being more adept at capturing non-linear relationships. On the other hand, **KNN** lags behind the other models with an accuracy of 58 % and the lowest precision and F1-scores, suggesting that it may not be well-suited for this dataset. However, KNN could still be effective in datasets where local patterns dominate, and computational efficiency is not a priority. Overall, the table underscores the trade-offs between accuracy, interpretability, and

Table 4

Classification results of machine learning models for pedestrian crash severity.

Metric	Logistic regression	Decision tree	Random forest	K-Nearest neighbors (KNN)
Accuracy	62 %	63 %	65 %	58 %
Precision	56 %	57 %	60 %	50 % (weighted)
	(weighted)	(weighted)	(weighted)	
Recall	62 %	63 %	65 %	58 % (weighted)
	(weighted)	(weighted)	(weighted)	
F1-Score	58 %	59 %	62 %	52 % (weighted)
	(weighted)	(weighted)	(weighted)	

Source: Authors.

computational resources, guiding the choice of algorithm based on the specific requirements of the analysis (Table 4).

SHAP values

The SHAP values are based on the Random Forest model (Fig. 5). Under the assumption that crash severity levels are classified as B (low severity), K (medium severity), and A (high severity), the SHAP analysis reveals the following insights. Age is the most influential variable across all severity levels, with older individuals strongly associated with high-severity (A) crashes, while younger pedestrians are linked to low-severity (B) crashes. Nighttime conditions (Night_dummy) also contribute significantly to severe crashes (A) due to reduced visibility, whereas low severity (B) crashes are less likely at night. Sex Female shows a stronger association with low severity (B) crashes, while its influence on high severity (A) outcomes is weaker. Road infrastructure plays a key role, as roads without physical dividers (PositionType_Not_Divided) and higher area speeds (AreaSpeed) are major contributors to high severity (A) crashes, while low severity (B) crashes are more common in safer environments with controlled speeds and dividers. Similarly, sloped alignments (VerticalAlign_Slope) and uncontrolled pedestrian crossings (UnitMovement_Crossing_without_Control) show strong associations with medium (K) and high severity (A) crashes.

show strong associations with medium (K) and high severity (A) crashes.

Crashes in metropolitan areas (SA_Metropolitan) are more likely to result in medium severity (K) outcomes, likely due to dense traffic and pedestrian interactions. The weekend and holiday times (Weekend/holiday) also influenced medium (K) and high severity (A) crashes, possibly due to altered traffic patterns. Seasonal effects such as Autumn were more associated with low severity (B) crashes, indicating safer conditions during this season. Overall, high-severity crashes (A) are strongly influenced by factors like Age, area speed, and Nighttime conditions. In contrast, medium-severity crashes (K) are shaped by urban and environmental factors such as PositionType_Not_Divided and SA_Metropolitan. Low-severity crashes (B) are linked to safer conditions, including female, Autumn, and lower speeds.

These findings align closely with previous research on pedestrian crash severity. Studies have consistently demonstrated the role of area speed, lighting conditions, and pedestrian age as critical determinants of crash outcomes. For instance, Ankunda et al. [65] found that pedestrian fatality risk increases exponentially with vehicle speed as well as Al-Marafi et al. [66]. A finding corroborated by the SHAP analysis showing the strong contribution of AreaSpeed to high-severity crashes [67]. Similarly, Sullivan and Falnagan [68] highlighted the increased

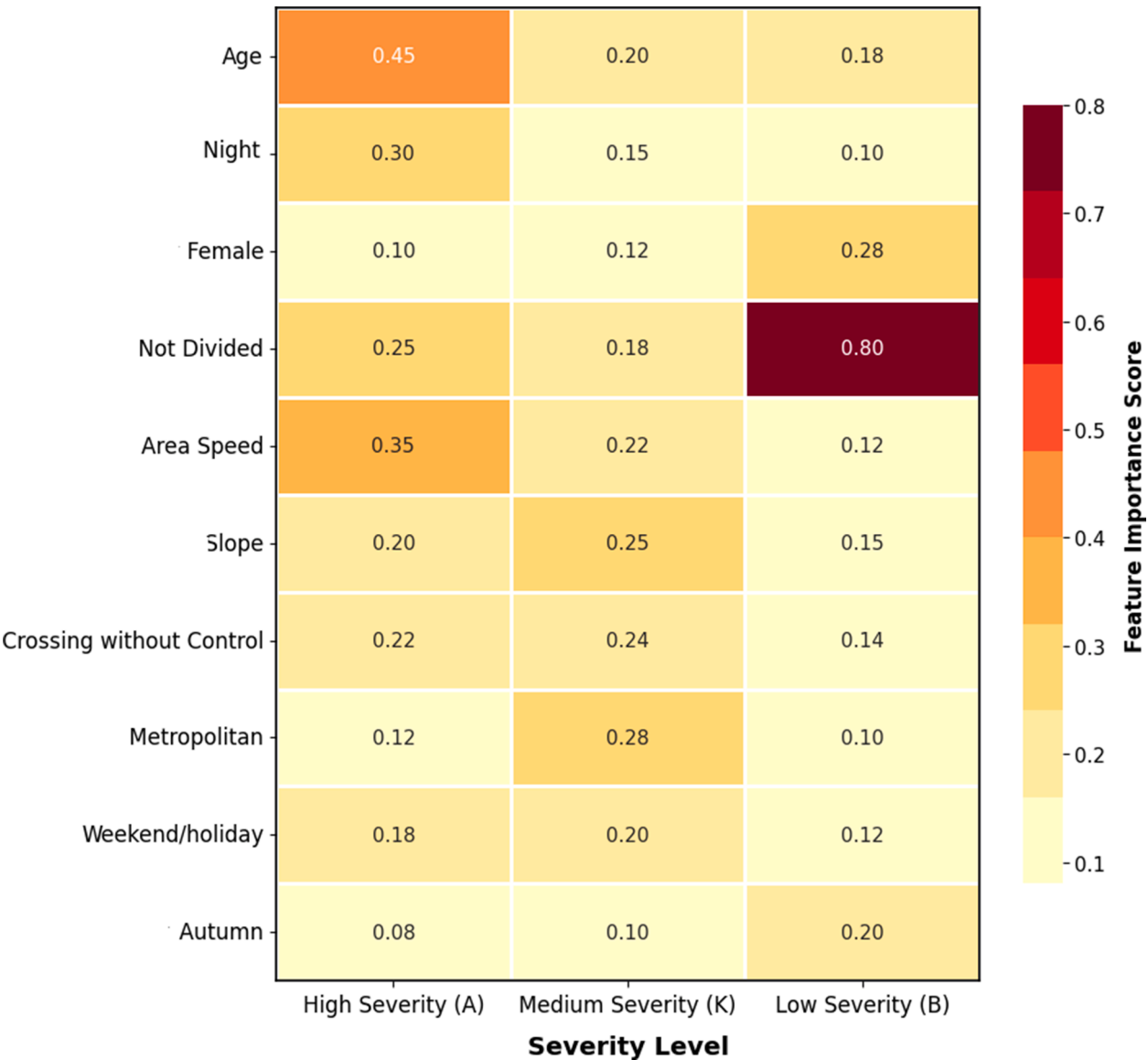


Fig. 5. SHAP value based on the crash severity classification from the Random Forest model (Source: Authors).

risk of nighttime crashes due to reduced visibility, aligning with SHAP results indicating Nighttime conditions as a key factor in severe crashes. The influence of uncontrolled pedestrian crossings, identified in SHAP through *PositionType_Not_Divided*, mirrors findings by Zegeer et al. [69], who emphasized the risks associated with marked but uncontrolled crosswalks on multi-lane roads. Moreover, SHAP's ability to capture non-linear interactions adds depth to the analysis. For example, the combined effect of Age and *PositionType_Not_Divided* shows a higher risk for older pedestrians at uncontrolled crossings, complementing findings from Fang et al. [52] on age-related vulnerabilities. The consistency of SHAP results with existing literature validates the method. It underscores the importance of targeted interventions, such as reducing speeds in high-risk zones, improving pedestrian infrastructure, and enhancing lighting in urban areas.

Discussion

Regarding the research questions, firstly, investigating the factors influencing the severity of pedestrian crashes has valuable insights for young and old pedestrians. The analysis has revealed several factors significantly contributing to the likelihood of fatal or seriously injured (KSI) outcomes in pedestrian crashes. For both age groups, the type of area where the crash occurs plays a crucial role. The findings suggest that urban environments pose higher risks for severe crashes, possibly due to increased traffic density and higher speeds. This is consistent with the findings of Sung et al. [70], which also associate higher density with a higher number of traffic crashes. However, it also suggests that higher density may lower the occurrence of pedestrian fatalities through other channels in dense urban environments, such as lowering traffic speeds.

Furthermore, many studies (e.g., [71–74]) believe higher speed significantly increases the likelihood of fatal pedestrian crashes. The results show that lower speeds (<60 km/hr) correlate with higher log-odds of KSI for young pedestrians, suggesting that reducing vehicle speeds could mitigate the severity of crashes in this age group. For old pedestrians, lower speeds (<60 km/hr) result in higher log-odds of KSI, indicating that slower vehicle speeds may be detrimental for this age group. Additionally, the day of the crash has a notable impact. Crashes occurring on weekends, as opposed to weekdays, tend to be associated with lower log-odds of KSI for both age groups. This may be attributed to differences in traffic patterns and volume during weekends. The speed of vehicles involved in crashes is a critical factor. Mailn et al. [75] found that the proportion of pedestrian KSI crashes is lower at weekends. However, the findings of Chen and Fan [76] and Li et al. [77] reveal that a high percentage of severe injury crashes happen on the weekends.

The analysis has highlighted age-specific patterns in the factors contributing to crash severity. While there are shared risk factors, distinctions also warrant attention. For young pedestrians, curved roads with obscured views are associated with lower log-odds of KSI, possibly due to increased vigilance and slower vehicle speeds in such conditions. Likely, Haynes et al. [78] found no evidence that frequently curved roads had more crashes than elsewhere. In contrast, crashes at night are linked to lower log-odds of KSI for young pedestrians, likely because nighttime crashes occur with fewer vehicles on the road and often involve lower speeds. Additionally, crashes on wet roads are associated with lower log-odds of KSI for older pedestrians, possibly due to decreased impact forces in wet conditions. This finding diverges from the conclusions drawn by Zhai et al. [79], who reported a significant increase in the probability of severe pedestrian crashes during rainy conditions.

Applying Classification and Regression Trees (CART) has provided further insights into the factors contributing to severe pedestrian crashes for both age groups. The most critical position types for young pedestrians are freeways and one-way roads, with specific scenarios including alighting from parked vehicles and pedestrian crossings. This suggests that interventions should focus on these high-risk locations and situations. For old pedestrians, crossroads and one-way roads emerge as

critical positions, particularly when crossing with signals, walking on the road, and alighting from parked vehicles. Undivided and one-way roads also present risks, especially when crossing without control or within 30 m of a pedestrian crossing. These findings emphasize the importance of improving intersectional safety measures and enhancing awareness among older pedestrians.

The research findings have important policy implications for enhancing road safety for pedestrians. Policymakers should prioritize urban planning and infrastructure improvements, particularly in metropolitan areas, to create pedestrian-friendly environments [80]. Policies promoting traffic calming measures, lower speed limits, and safer road conditions effectively reduce crash severity [81,82]. Weekend safety measures should be encouraged because weekend crashes are generally less severe. Speed management strategies, such as lower speed limits, are crucial, especially in areas with young pedestrians [83,84]. Enhanced visibility, well-maintained intersections, and targeted age-specific education campaigns are vital for crash prevention [85]. Policies should consider gender-specific differences in crash severity and adapt accordingly [86]. Data-driven decision-making and community engagement are essential for ongoing road safety improvement. Investing in pedestrian-friendly infrastructure, including sidewalks and improved signage, is key to creating safer environments for pedestrians of all ages. Studies suggest strategies and interventions for young pedestrians to reduce the risk of road crashes. It includes educational/behavioral approaches, legislation/law enforcement approaches, engineering/technology approaches, and multifaceted interventions [87–90]. For example, the “Green Light for Life” training program was emphasized as a simple intervention using parent influences to improve injury crash rates by 12.7 % among young adults aged 15–29 [91]. Furthermore, programs enhancing people's attitudes and habits toward safe crossing can be effective. Several studies have addressed the importance of individual beliefs, attitudes, subjective norms, perceived behavioral control, self-identity, and intentions [92]. These policy recommendations offer a comprehensive approach to improving road safety.

The inclusion of SHAP values in the analysis enhances the interpretation of pedestrian crash severity findings by providing a deeper understanding of variable contributions at both global and local levels. SHAP confirms the importance of key variables identified in Binomial Logit Regression and CART, such as Area Speed, Nighttime Conditions, and Position Type, while offering additional granularity by quantifying the magnitude and direction of each variable's effect. For instance, SHAP values consistently highlight the strong positive association between higher area speeds and severe crash outcomes, providing numerical validation for patterns identified through other methods. Furthermore, SHAP excels in capturing non-linear relationships and interactions that might be overlooked in regression models. For example, it reveals how the combination of Age and Position Type can exacerbate crash severity, particularly for older pedestrians at uncontrolled crossings. Unlike CART, which prioritizes variables hierarchically, SHAP quantifies their overall importance across all observations, offering a more balanced perspective. Additionally, its ability to explain individual predictions provides localized insights, enabling the design of targeted interventions, such as improving pedestrian infrastructure in high-risk areas or enforcing speed limits in urban zones.

Lower vehicle speeds significantly reduce the likelihood and severity of pedestrian injuries. In line with international evidence, our findings suggest that crashes occurring at speeds below 60 km/h are associated with notably lower odds of KSI outcomes—particularly for older pedestrians. This supports policy shifts toward implementing lower urban speed limits (e.g., 50 km/h), which have been shown to reduce pedestrian injury severity by up to 25 %. These results reinforce the importance of speed management as a critical component of age-inclusive road safety strategies. This study provides actionable insights for policymakers and urban safety planners. As summarized in Table 5, age-

Table 5
Potential countermeasures by age group and risk factor.

Risk factor	Young pedestrians (Age <18)	Older pedestrians (Age >65)	Potential measures
High-Speed Roads	High crash rates at ≥ 60 km/h	Greater risk at high-speed roads	Reduce speed limits in pedestrian zones; install traffic calming (e.g., speed humps)
Time of Day	Afternoon peak linked to severe crashes	Afternoon peak increases risk	Enhanced supervision near schools; pedestrian refuge islands; improve afternoon lighting
Road Alignment (Curved)	Lower KSI in curved roads (limited evidence)	Curved roads with obscured views slightly safer	Improve signage, visibility, and crossing design on all alignments
Vertical Alignment	Minor influence	Crest of hill and slope may increase risk	Add warning signs, speed controls, and improve pedestrian visibility
Crossing Without Control	Most crashes involve uncontrolled crossing (82.3 %)	Also dominant (77.9 %)	Install controlled crosswalks, pedestrian signals, and curb extensions
Environmental Conditions	Crashes mostly in dry conditions	Wet/nighttime conditions slightly increase risk	Use high-friction surfaces; better night lighting; public awareness campaigns
Traffic Control	Roundabouts linked to higher risk	Minor effects observed	Review roundabout design for pedestrian safety; evaluate signage and markings

(Source: Authors).

specific risk factors can inform infrastructure upgrades—such as improved lighting, crossing design, and speed management—as well as tailored public education to enhance safety for young and older pedestrians.

Limitations

The study is primarily limited by the lack of comprehensive data on pedestrian crashes, as this research is based on police-reported crash data, whilst a considerable number of pedestrian crashes are admitted to hospital without being reported to police authority [6]. Moreover, as this research focused only on one State of Australia comprising <8 percent of the Australian population, the generalisability of the findings may be limited by geographical variances and cultural variables that were not entirely accounted for. By categorizing age groups broadly, there is a risk of overlooking subtle differences within specific age brackets. In addition, the study's scope may exclude essential factors such as pedestrian behavior or the condition of road infrastructure.

While this study categorized pedestrians into two broad age groups—young (<18) and older (>65)—we acknowledge that more granular subgrouping (e.g., preschoolers, school-age children, adolescents; or young-old [65–74] vs. old-old [75+]) would provide deeper behavioral and risk differentiation. However, the available dataset did not include a sufficient number of cases in these finer age bands to allow statistically meaningful analysis. We highlight this as an important direction for future work, where larger samples or multi-source datasets may allow for more detailed modeling of age-specific pedestrian vulnerabilities. Adults aged 18–64 constitute a significant proportion of pedestrian crash victims; however, this demographic encompasses a wide range of behavioral patterns, mobility characteristics, and levels of risk exposure. The inclusion of such a heterogeneous group may mask critical intra-group variations. To enhance analytical precision and maintain relevance for policy development, the present study focuses on younger

(<18) and older (>65) pedestrians, as these cohorts demonstrate more uniform vulnerability profiles.

Another important limitation concerns the inability to perform a joint age-and-sex subgroup analysis within the young and older pedestrian groups. While such stratification could provide more nuanced insights into risk factors and improve the targeting of safety interventions, the number of observations within specific age-sex combinations was too limited to yield statistically reliable results. Future studies with larger or pooled datasets are encouraged to explore these interactions in greater depth. While focusing on high-risk age groups (<18/>65) reveals distinct vulnerability patterns, we recognize adults (19–65) - particularly 19–30-year-olds (19 % fatalities) and 31–50-year-olds (24 % moderate injuries) - may represent important transitional risk categories meriting separate analysis. Future studies should examine these subgroups' unique crash dynamics using age-stratified models.

Further research endeavors might go into other methodologies to get a more comprehensive comprehension of pedestrian safety. Additional investigation within the broad age categories identified in this study may identify minor factors that impact pedestrian crashes within specific age groups. Conducting a study on pedestrian actions and attitudes towards road safety might yield valuable insights into how these factors contribute to the severity of crashes [93]. Engaging in comparative study across Australian States or within the broader area of Oceania and Southeast Asia, considering their distinct geographical and cultural characteristics, might aid in differentiating between universal and context-specific elements contributing to pedestrian crashes. In addition, evaluating the effectiveness of measures, such as measures to decrease traffic or improvements to infrastructure, would offer direction for evidence-based policy recommendations. Further investigation into the use of supplementary data sources, such as hospital admission data, ambulance and insurance companies' data [94], and the analysis of the impact of emerging technologies, such as autonomous cars [95], on interactions about pedestrian safety, present promising avenues for future research. Integrating detailed hospital data is paramount, as it provides a far more nuanced understanding of injury severity and patient outcomes than is available from crash reports alone [96,97]. By employing data linkage to connect these clinical records with police data [98], future research can precisely correlate crash circumstances with specific types of trauma, leading to more targeted and effective safety interventions. Engagement with these instructions might significantly enhance comprehension and provide targeted strategies to mitigate the gravity of pedestrian crashes in South Australia or a similar region.

Conclusions

Understanding the determinants of pedestrian crash severity is vital for formulating effective safety interventions. This study applies an advanced predictive model to analyze Killed or Seriously Injured (KSI) pedestrian incidents in South Australia, focusing on two age cohorts: the young and the elderly. Age-specific analysis enables the identification of critical risk factors and behavioral patterns, offering valuable insights for policymakers, safety professionals, and transport planners. The findings reveal marked gender disparities. Male pedestrians exhibit a higher mean number of annual hospitalizations (1468.09) compared to females (1125.64). However, when considering pedestrian hospitalizations as a proportion of total road user admissions, females demonstrate a higher percentage (8.59 %) than males (6.05 %). Age-stratified data indicate that males aged 65 and above face elevated hospitalization rates relative to those aged 16–65.

Spatial and temporal crash patterns vary between age groups. Among younger pedestrians, KSI incidents are more frequent in rural areas, particularly during weekends, at speeds exceeding 60 km/h, and under curved or wet road conditions. Nighttime and uncontrolled traffic environments also present heightened risks, especially for males. Conversely, older pedestrians are vulnerable in both rural and urban contexts, with increased crash severity observed on weekends and under

similar hazardous roadway and environmental conditions. Morning peak hours emerge as a critical risk period for older individuals. In conclusion, the model's outputs underscore the importance of age- and gender-sensitive approaches to pedestrian safety. The insights gained can inform the development of targeted policies, infrastructure improvements, and educational campaigns aimed at reducing the frequency and severity of pedestrian crashes across diverse demographic groups.

CRedit authorship contribution statement

Ali Soltani: Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ahmed Jaber:** Visualization, Validation, Resources, Formal analysis, Data curation, Conceptualization. **Hamed Najafi Kashkooli:** Writing – review & editing, Writing – original draft, Validation, Project administration, Conceptualization. **Madaha Bencekri:** Validation, Resources, Project administration, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The corresponding author will disclose any data, models, or scripts used in the work upon a reasonable request.

Ethics

This manuscript has not been published elsewhere and is not under consideration by any other journal. All authors have read and approved the final manuscript and agree to its submission to *Injury*. There are no conflicts of interest to declare. The raw data used in this study are available from the corresponding author upon reasonable request.

References

- [1] Al-Mahameed FJ, Qin X, Schneider RJ, Shaon MRR. Analyzing pedestrian and bicyclist crashes at the corridor level: structural equation modeling approach. *Transp Res Rec J Transp Res Board* Jul. 2019;2673(7):308–18. <https://doi.org/10.1177/0361198119845353>.
- [2] Bernhardt M, Kockelman K. An analysis of pedestrian crash trends and contributing factors in Texas. *J Transp Health Sep*. 2021;22:101090. <https://doi.org/10.1016/j.jth.2021.101090>.
- [3] Chen Y, Yuan R, Wei J, Li S. Research on the influencing factors of older people pedestrian traffic accidents considering the built environment. *Int Rev Spat Plan Sustain Dev Jan*. 2023;11(1):44–63. <https://doi.org/10.14246/irspds.11.1.44>.
- [4] Doulabi S, Hassan HM, Ferguson MR, Razavi S, Paez A. Exploring the determinants of older adults' susceptibility to pedestrians' incidents. *Accid Anal Prev Jun*. 2021; 155:106100. <https://doi.org/10.1016/j.aap.2021.106100>.
- [5] Hu L, Wu X, Huang J, Peng Y, Liu W. Investigation of clusters and injuries in pedestrian crashes using GIS in Changsha, China. *Saf Sci* 2020;127:104710. <https://doi.org/10.1016/j.ssci.2020.104710>.
- [6] Jaber A, Al-Sahili K. Severity of pedestrian crashes in developing countries: analysis and comparisons using decision tree techniques. *SAE Int J Transp Saf Dec*. 2022;11(2). <https://doi.org/10.4271/09-11-02-0008>. 09-11-02-0008.
- [7] Kim S, Ulfarsson GF. Traffic safety in an aging society: analysis of older pedestrian crashes. *J Transp Saf Secur May* 2019;11(3):323–32. <https://doi.org/10.1080/19439962.2018.1430087>.
- [8] Twisk D, Vlakveld W, Mesken J, Shope JT, Kok G. Inexperience and risky decisions of young adolescents, as pedestrians and cyclists, in interactions with lorries, and the effects of competency versus awareness education. *Accid Anal Prev Jun*. 2013; 55:219–25. <https://doi.org/10.1016/j.aap.2013.02.038>.
- [9] BITRE. International road safety comparisons. Bureau of Infrastructure and Transport Research Economics; 2023 [Online]. Available, https://www.bitre.gov.au/publications/ongoing/international_road_safety_comparisons.
- [10] Tournier I, Dommes A, Cavallo V. Review of safety and mobility issues among older pedestrians. *Accid Anal Prev Jun*. 2016;91:24–35. <https://doi.org/10.1016/j.aap.2016.02.031>.
- [11] Zito GA, et al. Street crossing behavior in younger and older pedestrians: an eye- and head-tracking study. *BMC Geriatr Dec*. 2015;15(1):176. <https://doi.org/10.1186/s12877-015-0175-0>.
- [12] Kahlert D, Schlicht W. Older people's perceptions of pedestrian friendliness and traffic safety: an experiment using computer-simulated walking environments. *Int J Environ Res Public Health Aug*. 2015;12(8):10066–78. <https://doi.org/10.3390/ijerph120810066>.
- [13] Strohmeier F. Barriers and their influence on the mobility behavior of elder pedestrians in urban areas: challenges and best practice for walkability in the City of Vienna. *Transp Res Procedia* 2016;14:1134–43. <https://doi.org/10.1016/j.trpro.2016.05.184>.
- [14] Soltani A, Azmoodeh M, Qadikolaei MR. Road crashes in Adelaide metropolitan region, the consequences of COVID-19. *J Transp & Health* 2023;30:101581. <https://doi.org/10.1016/j.jctsp.2018.01.006>.
- [15] Chimba D, Musinguzi A, Kidando E. Associating pedestrian crashes with demographic and socioeconomic factors. *Case Stud Transp Policy Mar*. 2018;6(1): 11–6. <https://doi.org/10.1016/j.cstp.2018.01.006>.
- [16] Soltani A, RoohaniQadikolaei M, Sobhani A. Shifting Landscapes, Escalating Risks: How Land Use Conversion Shapes Long-Term Road Crash Outcomes in Melbourne. *Future Transp* 2025;5(2):75. <https://doi.org/10.3390/futuretransp5020075>.
- [17] Soltani A, Qadikolaei MR. Space-time analysis of accident frequency and the role of built environment in mitigation. *Transp Policy* 2024;150:189–205.
- [18] Lord S, Cloutier M-S, Garnier B, Christoforou Z. Crossing road intersections in old age—With or without risks? Perceptions of risk and crossing behaviours among the older people. *Transp Res Part F Traffic Psychol Behav May* 2018;55:282–96. <https://doi.org/10.1016/j.trf.2018.03.005>.
- [19] Hyun TG, et al. Factors and their correlation with injury severity of older people pedestrian traffic accidents. *J Trauma Inj Sep*. 2019;32(3):143–9. <https://doi.org/10.20408/jti.2019.022>.
- [20] Lee HH, et al. Relationship between age and injury severity in traffic accidents involving older people pedestrians. *Clin Exp Emerg Med* 2019;6(3):235–41. <https://doi.org/10.15441/ceem.18.052>.
- [21] Loo BPY, Tsui KL. Pedestrian injuries in an ageing society: insights from hospital trauma registry. *J Trauma Inj Infect Crit Care Apr*. 2009;66(4):1196–201. <https://doi.org/10.1097/TA.0b013e318171def6>.
- [22] Guo M, Yuan Z, Janson B, Peng Y, Yue R, Zhang G. Do factors associated with older pedestrian crash severity differ? A causal factor analysis based on exposure level of pedestrians. *Traffic Inj Prev May* 2023;24(4):321–30. <https://doi.org/10.1080/15389588.2023.2183080>.
- [23] Chandler Z, Van Den Heuvel C, Baldock M, James S, Byard RW. The effect of age on injury patterns in pedestrian deaths. *Med Sci Law Oct*. 2023;63(4):287–91. <https://doi.org/10.1177/00258024221143968>.
- [24] Nogueira Silva M, Craveiro Cunto FJ, Timbó Lima Gomes MJ, Ferreira S. An analysis of the injury severity of pedestrians in Brazil using random parameters logit models. *Transportes Jan*. 2023;31(1). <https://doi.org/10.14295/transportes.v31i1.2761>.
- [25] Doroudgar S, Chuang HM, Perry PJ, Thomas K, Bohnert K, Canedo J. Driving performance comparing older versus younger drivers. *Traffic Inj Prev Jan*. 2017;18(1):41–6. <https://doi.org/10.1080/15389588.2016.1194980>.
- [26] Soltani A, Askari S. Analysis of intra-urban traffic accidents using spatiotemporal visualization techniques. *Transport and Telecommunication* 2014;15(3):227–32.
- [27] Jaber A, Csonka B. How do land use, built environment and transportation facilities affect bike-sharing trip destinations? *Promet - TrafficTransportation* 2023; 35(1):119–32. <https://doi.org/10.7307/ptt.v35i1.67>.
- [28] Wilmut K, Purcell C. Why are older adults more at risk as pedestrians? A systematic review. *Hum Factors J Hum Factors Ergon Soc Dec*. 2022;64(8):1269–91. <https://doi.org/10.1177/0018720821989511>.
- [29] Folli M, Bennett JM. Factors that predict hazard perception in older adult road-users: a systematic review. *Transp Res Part F Traffic Psychol Behav Nov*. 2023;99: 19–35. <https://doi.org/10.1016/j.trf.2023.10.008>.
- [30] Holland C, Hill R. Gender differences in factors predicting unsafe crossing decisions in adult pedestrians across the lifespan: a simulation study. *Accid Anal Prev Jul*. 2010;42(4):1097–106. <https://doi.org/10.1016/j.aap.2009.12.023>.
- [31] Valos N, Bennett JM. The relationship between cognitive functioning and street-crossing behaviours in adults: a systematic review and meta-analysis. *Transp Res Part F Traffic Psychol Behav Nov*. 2023;99:356–73. <https://doi.org/10.1016/j.trf.2023.10.018>.
- [32] Oxley JA, Ihlen E, Fildes BN, Charlton JL, Day RH. Crossing roads safely: an experimental study of age differences in gap selection by pedestrians. *Accid Anal Prev Sep*. 2005;37(5):962–71. <https://doi.org/10.1016/j.aap.2005.04.017>.
- [33] Soltani A, Mansourihanis O, RoohaniQadikolaei M, Zaroujtaghi A. Two decades of geospatial evolution: tracing the analytical journey towards data-driven road crash prevention. *Appl Spat Anal Policy* 2024;17(3):1301–34.
- [34] Jr and McGwin G, Brown DB. Characteristics of traffic crashes among young, middle-aged, and older drivers. *Accid Anal Prev May* 1999;31(3):181–98. [https://doi.org/10.1016/S0001-4575\(98\)00061-X](https://doi.org/10.1016/S0001-4575(98)00061-X).
- [35] Haleem K, Alluri P, Gan A. Analyzing pedestrian crash injury severity at signalized and non-signalized locations. *Accid Anal Prev Aug*. 2015;81:14–23. <https://doi.org/10.1016/j.aap.2015.04.025>.
- [36] Sarkar S, Tay R, Hunt JD. Logistic regression model of risk of fatality in vehicle–Pedestrian crashes on national highways in Bangladesh. *Transp Res Rec J Transp Res Board Jan*. 2011;2264(1):128–37. <https://doi.org/10.3141/2264-15>.
- [37] Soltani A, Askari S. Exploring spatial autocorrelation of traffic crashes based on severity. *Injury Mar*. 2017;48(3):637–47. <https://doi.org/10.1016/j.injury.2017.01.032>.

- [38] Tarko A, Azam MdS. Pedestrian injury analysis with consideration of the selectivity bias in linked police-hospital data. *Accid Anal Prev Sep.* 2011;43(5):1689–95. <https://doi.org/10.1016/j.aap.2011.03.027>.
- [39] Meir A, Oron-Gilad T. Understanding complex traffic road scenes: the case of child-pedestrians' hazard perception. *J Safety Res Feb.* 2020;72:111–26. <https://doi.org/10.1016/j.jsr.2019.12.014>.
- [40] Cloutier M-S, et al. State-of-the-art review: preventing child and youth pedestrian motor vehicle collisions: critical issues and future directions. *Inj Prev Feb.* 2021;27(1):77–84. <https://doi.org/10.1136/injuryprev-2020-043829>.
- [41] Luburić G, Blašković APerković, Hasani H. Risk assessment of traffic accidents involving young adult drivers by identification of subjective and objective factors. *Promet Feb.* 2023;35(1):27–36. <https://doi.org/10.7307/ptt.v35i1.9>.
- [42] Meir A, Oron-Gilad T, Parmet Y. Can child-pedestrians' hazard perception skills be enhanced? *Accid Anal Prev Oct.* 2015;83:101–10. <https://doi.org/10.1016/j.aap.2015.07.006>.
- [43] Stevens E, Plumert JM, Cremer JF, Kearney JK. Preadolescent temperament and risky behavior: bicycling across traffic-filled intersections in a virtual environment. *J Pediatr Psychol Apr.* 2013;38(3):285–95. <https://doi.org/10.1093/jpepsy/jss116>.
- [44] Tabibi Z, Pfeffer K. Choosing a safe place to cross the road: the relationship between attention and identification of safe and dangerous road-crossing sites. *Child Care Health Dev Jul.* 2003;29(4):237–44. <https://doi.org/10.1046/j.1365-2214.2003.00336.x>.
- [45] Oxley J, Fildes B, Ihlen E, Charlton J, Day R. Differences in traffic judgements between young and old adult pedestrians. *Accid Anal Prev Nov.* 1997;29(6): 839–47. [https://doi.org/10.1016/S0001-4575\(97\)00053-5](https://doi.org/10.1016/S0001-4575(97)00053-5).
- [46] Akhtar A, Brooks A, Kitchen S, O'Connor RC. The diurnal and seasonal relationships of pedestrian injuries secondary to motor vehicles in young people. *Trauma Apr.* 2024;26(2):142–9. <https://doi.org/10.1177/14604086221148954>.
- [47] Wang H, Tan D, Schwebel DC, Shi L, Miao L. Effect of age on children's pedestrian behaviour: results from an observational study. *Transp Res Part F Traffic Psychol Behav Oct.* 2018;58:556–65. <https://doi.org/10.1016/j.trf.2018.06.039>.
- [48] Chinn L, Elliott, M.A., Sentinella, J., & Williams, K., "Road safety behaviour of adolescent children in groups: final report," 2004.
- [49] Dommes A, Cavallo V, Vienne F, Aillerie I. Age-related differences in street-crossing safety before and after training of older pedestrians. *Accid Anal Prev Jan.* 2012;44(1):42–7. <https://doi.org/10.1016/j.aap.2010.12.012>.
- [50] Kim D. The transportation safety of older people pedestrians: modeling contributing factors to older people pedestrian collisions. *Accid Anal Prev 2019*; 131:268–74. <https://doi.org/10.1016/j.aap.2019.07.009>.
- [51] Niebuhr T, Junge M, Rosén E. Pedestrian injury risk and the effect of age. *Accid Anal Prev Jan.* 2016;86:121–8. <https://doi.org/10.1016/j.aap.2015.10.026>.
- [52] Fang T, Xu F, Zou Z. Causal factors in older people pedestrian traffic injuries based on association analysis. *Appl Sci Jan.* 2025;15(3):1170. <https://doi.org/10.3390/app15031170>.
- [53] Rapos V, Cinelli ME, Grunberg R, Bourgaize S, Crétual A, Olivier A-H. Collision avoidance behaviours between older adult and young adult walkers. *Gait Posture Jul.* 2021;88:210–5. <https://doi.org/10.1016/j.gaitpost.2021.05.033>.
- [54] Cottrill CD, Thakuriah P. Evaluating pedestrian crashes in areas with high low-income or minority populations. *Accid Anal Prev 2010*;42(6):1718–28. <https://doi.org/10.1016/j.aap.2010.04.012>.
- [55] Toran Pour A, Moridpour S, Tay R, Rajabifard A. Influence of pedestrian age and gender on spatial and temporal distribution of pedestrian crashes. *Traffic Inj Prev Jan.* 2018;19(1):81–7. <https://doi.org/10.1080/15389588.2017.1341630>.
- [56] Ulak MB, Ozguven EE, Vanli OA, Dulebenets MA, Spainhour L. Multivariate random parameter tobit modeling of crashes involving aging drivers, passengers, bicyclists, and pedestrians: spatiotemporal variations. *Accid Anal Prev Dec.* 2018; 121:1–13. <https://doi.org/10.1016/j.aap.2018.08.031>.
- [57] Barton BK, Schwebel DC. The roles of age, gender, inhibitory control, and parental supervision in children's pedestrian safety. *J Pediatr Psychol Nov.* 2006;32(5): 517–26. <https://doi.org/10.1093/jpepsy/jsm014>.
- [58] ABS. Australian bureau of statistics. Australian Bureau of Statistics; 2021 [Online]. Available, <https://www.abs.gov.au/census/find-census-data/quickstats/2021/CED802>.
- [59] DataSa. South Australian government data directory. 2022 [Online]. Available, <https://data.sa.gov.au/>.
- [60] Yoon J. Prediction of high-risk areas using the interpretable machine learning: based on each determinant for the severity of pedestrian crashes. *J Transp Geogr Jun.* 2025;126:104216. <https://doi.org/10.1016/j.jtrangeo.2025.104216>.
- [61] Yue H. Investigating the influence of streetscape environmental characteristics on pedestrian crashes at intersections using street view images and explainable machine learning. *Accid Anal Prev Sep.* 2024;205:107693. <https://doi.org/10.1016/j.aap.2024.107693>.
- [62] Jaber A, Hamadneh J. Demographic analysis of active transport mode users in urban context," *period.* Polytech Transp Eng Jun. 2024;52(4):326–32. <https://doi.org/10.3311/PPtr.23401>.
- [63] Figueira A, Pitombo C, Oliveira P, Larocca A. Identification of rules induced through decision tree algorithm for detection of traffic accidents with victims: a case study from Brazil. *Case Stud Transp Policy 2017*;5(2):200–7. <https://doi.org/10.1016/j.cstp.2017.02.004>.
- [64] Breiman L, Friedman J, Olshen R, Stone C. Classification and regression trees. *statistics/probability series.* Monterey: Wadsworth & Brooks/Cole Advanced Books & Software; 1984.
- [65] Ankunda A, Ali Y, Mohanty M. Pedestrian crash risk analysis using extreme value models: new insights and evidence. *Accid Anal Prev Aug.* 2024;203:107633. <https://doi.org/10.1016/j.aap.2024.107633>.
- [66] Al-Marafi MN, Alhadidi TI, Alhawamdeh M, Jaber A. Enhancing road safety strategies through applying combined treatments for different crash severity. *Urban Sci Aug.* 2024;8(3):109. <https://doi.org/10.3390/urbansci8031019>.
- [67] Hussain Q, Feng H, Grzebieta R, Brijts T, Olivier J. The relationship between impact speed and the probability of pedestrian fatality during a vehicle-pedestrian crash: a systematic review and meta-analysis. *Accid Anal Prev Aug.* 2019;129:241–9. <https://doi.org/10.1016/j.aap.2019.05.033>.
- [68] Sullivan JM, Flannagan MJ. The role of ambient light level in fatal crashes: inferences from daylight saving time transitions. *Accid Anal Prev Jul.* 2002;34(4): 487–98. [https://doi.org/10.1016/S0001-4575\(01\)00046-X](https://doi.org/10.1016/S0001-4575(01)00046-X).
- [69] Zegeer C, Steward J, Lagerwerf P. Safety effect of marked versus unmarked crosswalks at uncontrolled locations: analysis of pedestrian crashes in 30 cities. *J Transp Res Board 2001*;1773(1):56–68.
- [70] Sung H, Lee S, Cheon S, Yoon J. Pedestrian safety in compact and mixed-use urban environments: Evaluation of 5D measures on pedestrian crashes. *Sustainability 2022*;14(2):646.
- [71] Kassar A, Hasan M. Factors associated with traffic crashes on urban freeways. *Transp Eng Dec.* 2020;2:100014. <https://doi.org/10.1016/j.treng.2020.100014>.
- [72] Mukherjee D, Mitra S. Comprehensive study of risk factors for fatal pedestrian crashes in urban setup in a developing country. *Transp Res Rec J Transp Res Board Aug.* 2020;2674(8):100–18. <https://doi.org/10.1177/0361198120925804>.
- [73] Rahman M, Kockelman KM, Perrine KA. Investigating risk factors associated with pedestrian crash occurrence and injury severity in Texas. *Traffic Inj Prev Jul.* 2022; 23(5):283–9. <https://doi.org/10.1080/15389588.2022.2059474>.
- [74] Zhao X, Yan X, Yu A, Hentenryck PV. Prediction and behavioral analysis of travel mode choice: a comparison of machine learning and logit models. *Travel Behav Soc July* 2020;20:22–35. <https://doi.org/10.1016/j.tbs.2020.02.003>.
- [75] Malin F, Silla A, Mladenović MN. Prevalence and factors associated with pedestrian fatalities and serious injuries: case Finland. *Eur Transp Res Rev Dec.* 2020;12(1): 29. <https://doi.org/10.1186/s12544-020-00411-z>.
- [76] Chen Z, Fan W. A multinomial logit model of pedestrian-vehicle crash severity in North Carolina. *Int J Transp Sci Technol 2019*;8(1):43–52. <https://doi.org/10.1016/j.ijtst.2018.10.001>.
- [77] Li Y, Song L, Fan W. Day-of-the-week variations and temporal instability of factors influencing pedestrian injury severity in pedestrian-vehicle crashes: a random parameters logit approach with heterogeneity in means and variances. *Anal Methods Accid Res 2021*;29:100152. <https://doi.org/10.1016/j.amar.2020.100152>.
- [78] Haynes R, Lake IR, Kingham S, Sabel CE, Pearce J, Barnett R. The influence of road curvature on fatal crashes in New Zealand. *Accid Anal Prev May* 2008;40(3): 843–50. <https://doi.org/10.1016/j.aap.2007.09.013>.
- [79] Zhai X, Huang H, Sze NN, Song Z, Hon KK. Diagnostic analysis of the effects of weather condition on pedestrian crash severity. *Accid Anal Prev Jan.* 2019;122: 318–24. <https://doi.org/10.1016/j.aap.2018.10.017>.
- [80] Pollack KM, Gielen AC, Mohd Ismail MN, Fitzner M, Wu M, Links JM. Investigating and improving pedestrian safety in an urban environment. *Inj Epidemiol Dec.* 2014;1(1):11. <https://doi.org/10.1186/2197-1714-1-11>.
- [81] Damers-Derry J, Ebel BE, Mock CN, Afukaar F, Donkor P, Kalowole TO. Evaluation of the effectiveness of traffic calming measures on vehicle speeds and pedestrian injury severity in Ghana. *Traffic Inj Prev Mar.* 2019;20(3):336–42. <https://doi.org/10.1080/15389588.2019.1581925>.
- [82] Jateikienė L, Andriejauskas T, Lingytė I, Jasūnienė V. Impact assessment of speed calming measures on road safety. *Transp Res Procedia 2016*;14:4228–36. <https://doi.org/10.1016/j.trpro.2016.05.394>.
- [83] Karndacharuk A, McTiernan D. Implementation principles for 30 km/h speed limits and zones. *J Australas Coll Road Saf May* 2019;30(2):45–54. <https://doi.org/10.33492/JACRS-D-18-00065>.
- [84] Ab Rashid AA, Poi AWH, Jawi ZM, Abu Kassim KA. Revisiting speed management strategies in Malaysia. *J Soc Automot Eng Malays May* 2021;5(2):318–30. <https://doi.org/10.56381/jsaem.v5i2.175>.
- [85] Lee G, Park Y, Kim J, Cho G-H. Association between intersection characteristics and perceived crash risk among school-aged children. *Accid Anal Prev Dec.* 2016; 97:111–21. <https://doi.org/10.1016/j.aap.2016.09.001>.
- [86] Onieva-García MÁ, et al. Gender and age differences in components of traffic-related pedestrian death rates: exposure, risk of crash and fatality rate. *Inj Epidemiol Dec.* 2016;3(1):14. <https://doi.org/10.1186/s40621-016-0079-2>.
- [87] Saadati M, Razzaghi A, Rezapour R, PourEbrahim K. Interventions for safety promotion of pedestrians; A scoping review. *J Transp Health Mar.* 2022;24: 101277. <https://doi.org/10.1016/j.jth.2021.101277>.
- [88] Schwebel DC, Davis AL, O'Neal EE. Child pedestrian injury: a review of behavioral risks and preventive strategies. *Am J Lifestyle Med Jul.* 2012;6(4):292–302. <https://doi.org/10.1177/0885066611404876>.
- [89] Selveindran SM, et al. Mapping global evidence on strategies and interventions in neurotrauma and road traffic collisions prevention: a scoping review protocol. *BMJ Open Nov.* 2019;9(11):e031517. <https://doi.org/10.1136/bmjopen-2019-031517>.
- [90] Soathong A, Chowdhury S, Wilson D, Ranjitkar P. Pedestrians' Road crossing behavior at unprotected mid-blocks among adolescents and adults. *Transp Res Rec J Transp Res Board Mar.* 2023;2677(3):1731–45. <https://doi.org/10.1177/03611981221138524>.
- [91] Gifty G, Zubair SM, Poobalan A, Sumit K. Effective interventions in road traffic accidents among the young and novice drivers of low and middle-income countries: a scoping review. *Clin Epidemiol Glob Health Oct.* 2021;12:100865. <https://doi.org/10.1016/j.cegh.2021.100865>.
- [92] McIlroy RC, et al. How do fatalistic beliefs affect the attitudes and pedestrian behaviours of road users in different countries? A cross-cultural study. *Accid Anal Prev May* 2020;139:105491. <https://doi.org/10.1016/j.aap.2020.105491>.

- [93] Zhou H, Romero SB, Qin X. An extension of the theory of planned behavior to predict pedestrians' violating crossing behavior using structural equation modeling. *Accid Anal Prev* Oct. 2016;95:417–24. <https://doi.org/10.1016/j.aap.2015.09.009>.
- [94] Montella A, Aria M, D'Ambrosio A, Mauriello F. Data-mining techniques for exploratory analysis of pedestrian crashes. *Transp Res Rec J Transp Res Board* 2011;2237(1):107–16. <https://doi.org/10.3141/2237-12>.
- [95] Tran T, Parker C, Tomitsch M. A review of virtual reality studies on autonomous vehicle–Pedestrian interaction. *IEEE Trans Hum-Mach Syst* Dec. 2021;51(6): 641–52. <https://doi.org/10.1109/THMS.2021.3107517>.
- [96] Soltani A, Afshari S, Amiri MA. Human cost, machine insight: a data-driven analysis of Australian road crashes. *Case StudTrans Policy* 2025 Jun 1;20:101440.
- [97] Soltani A, Afshari S, Amiri MA. Time-series projecting road traffic fatalities in Australia: insights for targeted safety interventions. *Injury* 2025 Mar 1;56(3): 112166.
- [98] Soltani A, Harrison JE, Ryder C, Flavel J, Watson A. Police and hospital data linkage for traffic injury surveillance: a systematic review. *Accid Anal Prev* 2024 Mar 1;197:107426.